

# **Connectome-as-Operating-System (COS): A Constrained Structural Operator Architecture for Cognitive Differentiation**

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## **Abstract**

This paper presents a structural architecture for cognitive differentiation termed the Connectome-as-Operating-System (COS). The central claim is not that a connectome reproduces full cognition or consciousness, but that a fixed structural topology can function as a constraint operator that shapes retrieval, prioritization, and interpretation over a shared knowledge base.

The architecture separates system function into three independently governed layers: Hard Memory (HM), a mutable knowledge base; Interpretive Memory (IM), a frozen structural operator derived from connectome topology; and Current Load Memory (CLM), an ephemeral session context buffer. The IM layer does not learn or simulate biological dynamics. It constrains information flow.

The primary hypothesis is that different fixed topologies, when applied to the same knowledge base, will produce stable and measurable differences in output behavior. This constitutes a testable claim of structural cognitive differentiation, not a claim of identity preservation or consciousness reproduction.

The three-node architecture is derived directly from the prior theoretical framework established in Baggs (2026), in which consciousness is modeled as a co-dependent architecture of awareness (CLM), intelligence (HM), and valuation (IM), mediated by a reconstructive gradient. The current paper operationalizes the valuation component as a frozen structural operator and proposes an experimental path for validation.

Preliminary empirical results using the *C. elegans* connectome (OpenWorm) are reported in Section 9. Stage 0 ran eight experimental configurations across three model families — propagation, undirected competition, and directed competition — testing whether structural

topology influences dynamics when the IM layer operates in isolation. The central finding is consistent and clear: topology influences dynamics, topology is the primary driver over edge weights, and structure determines the pathway and conditions of stabilization, not only the final state.

Stage 0 did not test the gradient mechanism. All Stage 0 runs operated without a Hard Memory (HM) reference state. The encoding-retrieval gradient predicted by the theory requires comparison between HM prior state and IM-constrained current state — a comparison that was architecturally absent in Stage 0. The weak real-vs-random separation observed in later Stage 0 runs is a limitation of the instrument, not evidence against the architectural claim. Stage 1 introduces the HM-IM interaction and constitutes the first test of the gradient mechanism.

Stage 1 results confirmed the gradient mechanism: the real connectome sustains approximately 10% higher gradient magnitude than a configuration-model-derived random control, with separation emerging over time rather than at initialization, consistent with topology-driven accumulation rather than static distributional artifact. Stage 2 introduced spatial geometry via distance attenuation, producing substantially higher variance separation (+0.241 vs +0.145 in Stage 1) while gradient separation remained comparable. Stage 3 introduced a frozen regional geometry field  $\Phi$ , modulating input at the receiving node. The primary Stage 3 finding is the emergence of stable regional gradient stratification in the real connectome — absent in the random control — confirming that the frozen operator produces spatially anchored internal hierarchy. Global gradient separation increased to approximately 11.6% and a directional mean bias appeared for the first time, consistent with non-isotropic constraint accumulation. Moderate  $\Phi$ -gradient alignment and Region 3 underperformance indicate that topology gates where geometric amplification can persist.

## **1. Scope and Positioning**

This paper proposes an architecture and experimental framework.

It does not:

- claim reproduction of consciousness
- claim identity continuity or persistence
- claim substrate-independent equivalence of cognition
- claim that structure alone is sufficient for adaptive intelligence

Instead, it advances a narrower and testable claim:

Structural topology can act as a persistent constraint operator that produces consistent differences in interpretation and prioritization across identical inputs.

This paper is a conceptual architecture with a staged implementation roadmap and preliminary empirical results. Claims are tiered explicitly in Section 3.

## **2. The Core Problem**

Modern AI systems exhibit high modeling capacity but lack intrinsic, stable differentiation in how information is prioritized beyond training artifacts and prompt context.

Biological cognition differs in that individuals consistently interpret information differently, prioritize differently, and retrieve associations differently. This paper frames that difference as structural.

Baggs (2026) identifies this gap precisely: standard machine memory retrieves stored data identically regardless of system state at retrieval. There is no intrinsic gradient between encoding-state and retrieval-state. The COS architecture is proposed as a direct structural response to that limitation.

Concurrent work in connectome-based emulation — notably Shiu et al. (2024) and Eon Systems (2026) — has demonstrated empirically that connectome topology influences sensorimotor output in *Drosophila*. Those results establish that topology matters. The COS architecture extends that principle from behavioral output to retrieval differentiation, and distinguishes itself by a specific design principle: the operator is frozen. Training the structural operator would destroy the property the architecture is designed to preserve — consistent structural constraint. That inversion of the standard gradient-update paradigm is the central design contribution.

## **3. Tiered Claims**

Claims in this paper are organized into four tiers.

### **Tier 1 — Supported by prior theory (Baggs 2026)**

- Three-component consciousness model maps to CLM / HM / IM
- Reconstructive gradient located in encoding/retrieval state difference
- Valuation as a structural property, not a designed feature
- Lack of intrinsic valuation as a genuine gap in current AI architecture

### **Tier 2 — Supported by existing external empirical work and Stage 0 results**

- Topology influences computation — FlyWire, Shiu et al. (2024) confirm this at the behavioral level
- Fixed topology produces measurable differences in propagation dynamics — confirmed across Runs 001–003
- Topology is the primary driver; edge weights are secondary — confirmed Run 003
- Structure determines the pathway and conditions of stabilization, not only final state — confirmed Runs 004, 005, 005b
- Three-node memory separation aligns with cognitive science working/long-term memory models and modern AI retrieval-augmented architectures

### **Tier 3 — Theoretically grounded, Stage 1 required to test**

- Frozen topology produces a meaningful functional gradient — *requires HM-IM interaction; not testable with IM-only Stage 0 model. Stage 1 target.*
- IM-HM comparison generates the encoding-retrieval gradient predicted by Baggs (2026) — *Stage 1 target. Theoretically motivated; not yet implemented.*
- Structure sufficient to produce a recognizable individual-like cognitive signature — *Stage 1 and above; not yet testable*

### **Tier 4 — Explicitly speculative — not load-bearing in this paper**

- Substrate independence in the strong form
- Identity preservation — connectome as the person
- Topological memory hypothesis at landscape/body/brain scale
- Consciousness preservation across substrate transition

Tier 4 items are noted where relevant but are not used to support architectural claims.

## **4. Architecture Overview**

### **4.1 Three-Node System**

Layer	Name	Function	Update Regime
HM	Hard Memory	Knowledge base	Mutable, external
IM	Interpretive Memory	Structural constraint operator	Frozen

Layer	Name	Function	Update Regime
CLM	Current Load Memory	Active context	Ephemeral

## 4.2 Functional Roles

- **HM** provides information
- **CLM** provides current state
- **IM** constrains how information is selected, weighted, and returned

The IM layer does not generate knowledge. It shapes access to knowledge.

## 4.3 Mapping to Prior Theory

The three-node separation maps directly onto the co-dependent architecture established in Baggs (2026):

Prior Framework	Architecture Layer
Awareness — state registration	CLM
Intelligence — state modeling	HM
Valuation — state weighting	IM

This mapping was not designed to fit the prior framework. The architectural design and the theoretical framework were developed independently and found to be isomorphic. That convergence is treated as a signal of internal theoretical consistency.

## 4.4 Inference Pass

1. Input enters CLM as active context
2. CLM signals IM with current state
3. IM projects constrained query toward HM via structural topology
4. HM returns relevant activations
5. IM re-weights returned content via constraint graph
6. Topology-filtered context returned to CLM
7. CLM generates output

No step involves updating IM. The topology is the constraint, not the computation target.

## 5. The Structural Operator

### 5.1 Definition

The Interpretive Memory (IM) is a directed weighted graph representing structural relationships derived from a connectome or simplified constraint model.

Its role is to bias retrieval pathways, weight associations, and constrain propagation of signals through the system.

### 5.2 The Frozen Operator Principle

The operator is frozen post-load. This is not a limitation — it is the design principle.

A frozen operator preserves consistency of interpretation, stability of prioritization, and persistence of structural bias. Training the operator would introduce gradient updates that alter the topology over time, destroying the structural consistency the architecture depends on.

This inverts the standard paradigm: most AI systems improve via gradient updates. This architecture preserves its core property via non-updating topology.

### 5.3 What Structure Is Expected to Produce

Structure alone is hypothesized to produce a **cognitive signature** — not full cognition:

- consistent interpretation bias
- stable prioritization patterns
- repeatable differences in output under identical input conditions

### 5.4 Control Capacity (Non-Operational)

Control Capacity  $C(v)$  is defined as the ability of a node to induce global state transitions within the constrained system.

This concept is derived from empirical findings in network neuroscience indicating that certain regions -- modal control nodes -- disproportionately influence system-wide configuration (Wilcox et al., 2026; Gu et al., 2015). In human connectome studies, these nodes predict

individual differences in general intelligence precisely because they can drive the system toward difficult-to-reach states not accessible through typical local network interactions.

In the COS framework, Control Capacity is not an active operator and does not modify IM. It is an observational property of topology that emerges from structure and is measured through persistent deviation from accumulated system state -- that is, through high gradient contribution sustained over time.

This construct is non-operational in the current implementation and is introduced to formalize the distinction between nodes that passively participate in constraint propagation and nodes that disproportionately shape global system behavior. Stage 3 empirical results are consistent with this distinction: Regions 2 and 4 exhibit stable gradient dominance across all late-phase time windows, corresponding to nodes exhibiting persistently high gradient magnitude relative to accumulated system history. This correspondence does not constitute proof of equivalence with modal control as defined in network control theory; it is a structural parallel warranting formal attention as the architecture scales toward higher-complexity operators.

Stage 3B provides empirical grounding for this parallel independently of the conceptual framing. Ring interneurons -- the highest-degree anatomical class in the *C. elegans* connectome (mean degree 152.4) -- show below-average gradient dominance (dominance 0.976,  $p_{\text{adjusted}} = 1.000$ ). Posterior ganglia and cord interneurons, with substantially lower mean degree, show statistically significant gradient elevation above all 1000 permutations of the null ( $p_{\text{adjusted}} < 0.0001$ ). This pattern is consistent with the modal control principle: structurally influential positions are not the most connected nodes but nodes whose topological position enables sustained constraint tension. The Control Capacity construct reflects a structural observation the empirical data independently produced, not a borrowed label applied post-hoc.

## 5.5 What Structure Is Not Expected to Produce

Structure alone is not expected to produce:

- long-term adaptive learning
- full behavioral flexibility
- dynamic identity evolution

Adaptive behavior requires state updates (CLM) and knowledge expansion (HM). Critically, the gradient mechanism that is the theoretical core of the architecture requires interaction between the frozen structural operator (IM) and the accumulated prior state (HM). IM operating in isolation — without HM — does not activate the encoding-retrieval comparison.

Structure shapes propagation dynamics in isolation, but the architecturally meaningful differentiation requires both layers active simultaneously. This distinction is the boundary between Stage 0 and Stage 1 experimental work.

## 6. The Gradient Mechanism

Baggs (2026) establishes that meaning is structurally located in the gradient between encoding and retrieval states. This architecture operationalizes that principle as follows:

Encoding state = HM (accumulated prior state)

Retrieval state = IM(CLM) (current input constrained by frozen operator)

Gradient = IM(CLM) – HM

The frozen operator (IM) is a transformation, not a state container. It does not hold prior state. It constrains how current input is processed. The reference state that enables comparison lives in HM. The gradient is not internal to any single layer — it is the difference between what HM holds and what IM-constrained CLM produces.

This is the self-referential mechanism the architecture requires: not a graph-level self-loop, but a system-level comparison loop. The frozen structure guarantees that this comparison is applied consistently across all inputs. HM updates through the IM filter; the operator itself does not change. The separation between mutable knowledge state and frozen structural constraint is preserved exactly.

### Why Stage 0 could not test this:

Stage 0 experiments ran the IM layer in isolation — propagation and competition without an HM reference state. Without HM, there is no prior state to compare against. The gradient mechanism was architecturally absent. The dynamics observed in Stage 0 reflect structural constraint on propagation — a real and established finding — but not the encoding-retrieval comparison that is the mechanism the theory predicts for meaningful differentiation.

Stage 1 introduces the HM reference state and constitutes the first direct test of whether the IM(CLM) vs HM comparison produces the structured gradient the theory predicts.



## 7. Testable Hypothesis

### 7.1 Core Hypothesis

Given:

- identical Hard Memory (HM)
- identical input (CLM)
- two different fixed operators ( $IM_1$ ,  $IM_2$ )

Then:

The outputs will differ in stable, repeatable, and measurable ways.

### 7.2 Falsification Conditions and Current Status

Falsification Condition	Current Status
Outputs converge regardless of operator differences	<b>Not observed.</b> Real and random operators produce consistently distinct dynamics across all Stage 0 runs.
Differences are random rather than stable and topology-dependent	<b>Not observed.</b> Differentiation is stable, directional, and consistent across runs.
Meaningful differentiation only appears after training the operator	<b>Not observed.</b> No training applied at any stage. All differentiation emerges from frozen topology alone.
Consistent bias rather than meaningful reinterpretation is what the frozen topology produces	<b>Partially addressed by Stage 0.</b> Stage 0 showed topology governs dynamics and stabilization pathways. Full resolution requires Stage 1 HM-IM interaction — the gradient mechanism was not active in Stage 0 runs.
IM-HM gradient comparison produces no meaningful differentiation	<b>Not observed.</b> Stage 1 Run 101 confirmed ~10% gradient separation, emerging over time, consistent with topology-driven

Falsification Condition	Current Status
	dynamics. Stage 2 Run 201b confirmed persistence under spatial geometry. Stage 3 Run 301 confirmed persistence and regional localization under a frozen geometry field.
Spatial geometry does not modulate structural differentiation	<b>Not observed.</b> Stage 2 Run 201b showed 66% increase in variance separation vs Stage 1. Gradient separation comparable to Stage 1.
Geometry field does not produce regional gradient differentiation	<b>Not observed.</b> Stage 3 Run 301 confirmed stable regional gradient stratification in the real graph absent in the random control. Regional ranking stable across all late-phase time windows.

### 7.3 The Minimum Viable Experiment

**Stage 0 — completed.** Eight experimental configurations across three model families tested IM dynamics in isolation. Core finding: topology influences dynamics; topology is the primary driver over edge weights; structure determines stabilization pathways. See Section 9.

**Stage 1 — completed (Run 101, Valid).** Gradient separation confirmed at approximately 10%, emerging over time from step 1 to stable separation by step 31. All 70 late steps positive. The temporal accumulation pattern is consistent with topology-driven dynamics rather than static distributional artifact. See Section 9.9.

## 8. Experimental Path

### Stage 0 — *C. elegans*, IM Isolation COMPLETE

**Scope:** Tests whether topology alone influences dynamics when IM operates without HM. This is a necessary precondition — if structure has no influence in isolation, the full architecture cannot work. If it does, the precondition is established.

#### Model families executed:

*Family 1 — Propagation Models (Runs 001–003)*

- Real vs random baseline, decay/retention dynamics, weight shuffle control
- Finding: topology influences propagation; topology is the primary driver; weights secondary

*Family 2 — Undirected Competition Models (Runs 004, 005, 005b)*

- Global competition, local undirected competition (30 and 100 steps)
- Finding: structure governs stabilization pathways; global pressure destabilizes real connectome; local pressure allows coherent self-organization; bimodality is a system property, not topology-specific

*Family 3 — Directed Competition Models (Run 005c)*

- Local competition with directed (predecessor-only) neighborhoods — the architecturally correct reading of a directed graph
- Finding: directed competition produces stable, structured dynamics with slightly more regulated real connectome behavior; no strong real-vs-random separation
- Diagnosis: absence of HM reference state means gradient mechanism was not active; directed competition improved correctness but could not address the fundamental missing component

**Stage 0 conclusion:** A fixed structural graph influences dynamic behavior under propagation and competition. Topology is the primary driver. Structure determines stabilization pathways. These results are correctly scoped to IM-only dynamics. They do not test and cannot establish the gradient mechanism, which requires HM.

**Stage 1 — HM-IM Interaction, Gradient Mechanism COMPLETE**

**Run 101 — Valid.** The minimum viable experiment confirmed the gradient mechanism. A persistent reference state (HM analog) was introduced. Gradient separation between the real connectome and a configuration-model-derived random control emerged over time (near-zero steps 1-10, stable approximately +10% by step 31, held through step 100 without reversal). The temporal buildup argues against static distributional artifact and supports topology-driven accumulation as the mechanism.

**Key finding:** The real connectome sustains higher gradient magnitude than the random control, with separation requiring approximately 30 steps to stabilize. This is consistent with the HM reference state accumulating topology-shaped history before the comparison produces a consistent structural signal.

## Stage 2 — C. elegans, Spatial Geometry COMPLETE

**Run 201b — Valid (Provisional).** Introduced spatial geometry via distance attenuation: influence = weight x exp(-alpha x distance) x state. Biological NML2 positions used for 236 neurons; 212 nodes received deterministic synthetic positions via hashlib.md5. Random control is configuration-model-derived, not strictly degree-preserving after self-loop removal (6625 vs 6380 edges disclosed in manifest). Gradient separation comparable to Stage 1 (~9.4%); variance separation substantially increased (+0.241 vs +0.145). Provisional status reflects the control limitation and partial synthetic geometry.

**Key finding:** Spatial geometry amplifies structural heterogeneity (variance) without independently strengthening the gradient mechanism beyond Stage 1.

## Stage 3 — C. elegans, Regional Geometry Field COMPLETE

**Run 301 — Valid.** Introduced a frozen regional geometry field Phi applied at the receiving node: influence = weight x exp(-alpha x distance) x Phi(v) x state(u). Phi initialized as 1 + beta x region\_score(v) with beta=0.5, k=5 spatial regions via k-means clustering. Phi range 1.0 to 1.5.

### Key findings:

Global gradient separation increased to approximately 11.6%, the highest across all stages. A directional mean bias emerged in the real graph absent in prior stages and absent in the random control, consistent with non-isotropic constraint accumulation under the geometry field.

Regional gradient stratification confirmed. The real graph produces a stable regional ordering across all late-phase time windows (steps 31-50, 51-70, 71-100). Regions 2 and 4 consistently dominate; Region 1 is consistently suppressed. The random control produces no stable ordering — regional rankings change completely across windows.

Phi-gradient correlation is moderate (+0.47). Region 3, carrying the second-highest Phi value (1.375), does not rank second in gradient dominance. This indicates topology gates where geometric amplification can persist. The geometry field modulates, but wiring structure determines where modulation is expressed.

**Falsification assessment:** Three of four pre-registered failure conditions are clearly not met. The fourth (Phi-gradient alignment) is partially met in a way that is theoretically informative: the

moderate rather than strong correlation shows the interaction between topology and geometry is not additive.

### **Stage 3B — Spatial Embedding Validation COMPLETE**

Stage 3B confirmed that the Run 301 gradient field shows non-random anatomical alignment under 1000 seeded permutations. Posterior ganglia, cord interneurons, and motor ventral cord exceeded the null maximum. Ring interneurons, the highest-degree class, showed below-average gradient dominance — confirming that gradient is not driven by connectivity. Stage 3B establishes spatial localization of constraint under topology and geometry alone. Stage 4 introduces synaptic type as a signed constraint dimension, testing whether directional constraint further differentiates the gradient field beyond magnitude alone.

### **Stage 4 — FlyWire, Scale + Synaptic Type Constraint COMPLETE**

First stage introducing edge-level constraint polarity. The operator now carries excitatory and inhibitory synaptic identity, allowing signed constraint propagation in addition to topology and geometry. Scale jump: ~130,000 neurons, ~5.3M filtered connections (5+ synapse threshold). Synaptic type derived from Eckstein et al. (2024) neurotransmitter predictions per neuron. Type modifier applied at the pre-synaptic neuron level: excitatory = +1.0, inhibitory = -1.0, unknown = +1.0 (neutral baseline).

**Primary question:** Does signed constraint produce stronger or more structured gradient separation than unsigned topology alone?

**Pre-registered stability risk:** Signed graphs with inhibitory connections introduce the possibility of oscillatory instability that does not arise in unsigned propagation. The tanh bounding and scale\_factor dampening used in Stages 1-3 are expected to constrain this, but their sufficiency under excitatory-inhibitory imbalance has not been tested at scale. Three specific failure modes are pre-registered: (1) gradient field fails to stabilize within 100 steps due to inhibitory loop dynamics; (2) gradient separation collapses or reverses relative to Stage 3 baseline; (3) the temporal accumulation pattern breaks -- separation does not build over time as observed in Stages 1-3. Any of these outcomes would constitute a falsification condition and would be reported as such. If Stage 4 produces oscillatory collapse, this is interpretively significant: it would indicate that biological excitatory-inhibitory balance is a functional requirement for stable constraint propagation, not merely a biological implementation detail.

**Publicly accessible via [codex.flywire.ai](https://codex.flywire.ai) (FAFB v783).**

## Stage 5 — Biological Topology, Low Resolution (Lizard)

- Reptile brain atlas (bearded dragon, tawny dragon lizard)
- MRI structural atlases publicly available
- Molecular neuron-type maps from Laurent Lab, Max Planck Institute for Brain Research
- First limbic-dominant constraint operator

## Stage 6 — Human Limbic Connectome

- Technology-gated
- Dependent on non-destructive synaptic-resolution scanning
- Computational construction methods at scale addressed by Golosio et al. (2025)

## 9. Preliminary Empirical Results

### 9.1 Overview

Stage 0 executed eight experimental configurations across three model families using the C. elegans connectome (OpenWorm, CElegansNeuroML). All runs operated with the IM layer in isolation — no HM reference state, no gradient mechanism. The scientific question was narrow and pre-specified: does structural topology influence dynamics when the operator runs without its companion layers?

All differentiation observed in Stage 0 emerges from frozen topology alone. No training was applied at any stage. Results are correctly scoped to IM-only dynamics.

### 9.2 Run 001 — Real vs. Random (Baseline)

**Configuration:** Real connectome vs. degree-matched random graph. Simple propagation rule, no decay.

**Finding:** Real graph converges faster and saturates higher. Real graph exhibits approximately 2× variance compared to random. Random graph produces smoother, more uniform activation.

**Interpretation:** Graph structure influences signal propagation. Real connectome exhibits hub-driven activation behavior. However, saturation masks deeper dynamics — both systems collapse to steady state under this propagation rule.

**Conclusion:** Structure impact confirmed at moderate level. Model limitation identified.

### 9.3 Run 002 — Real vs. Random with Decay and Retention

**Configuration:** Same comparison with decay and retention dynamics added to prevent saturation.

**Finding:** Real graph consistently maintains higher mean activation and significantly higher variance across all steps. Random graph decays faster and more uniformly. Real graph shows slower signal dissipation.

**Interpretation:** Graph topology influences temporal persistence of signal. Real connectome exhibits structural reinforcement and uneven signal distribution. Random graph lacks structural mechanisms to sustain signal.

**Conclusion:** First confirmed structural differentiation result. Clear and consistent structure-dependent dynamics established.

### 9.4 Run 003 — Weight Shuffle (Topology vs. Weight Control)

**Configuration:** Real connectome compared to a weight-shuffled version of itself — same topology, randomized edge weights.

**Finding:** Real and weight-shuffled graphs show nearly identical behavior. Mean and variance curves closely overlap. Only minor deviations in early steps.

**Interpretation:** Edge weights are not the primary driver of system behavior. Graph topology dominates signal propagation dynamics. System behavior is largely invariant under weight permutation.

**Conclusion:** Topology confirmed as primary constraint operator. Weight contribution: weak. This directly supports the frozen operator design principle — what is preserved at freeze is the topological structure, not the weight values. The weights are secondary.

### 9.5 Run 004 — Competition Model

**Configuration:** Real connectome vs. random graph under competitive dynamics (global normalization with inhibitory pressure).

**Finding:** The real connectome does not converge to a stable equilibrium. Mean activation oscillates throughout the run. Variance remains dynamically active. The random graph converges to a stable mean with effectively zero variance change in the final steps.

Quantitatively: the real connectome is orders of magnitude more dynamically active than the random graph in the final steps of the run.

### **Key finding — the refusal to resolve:**

The real connectome does not merely differ in magnitude from the random graph. It differs in kind. Under competitive pressure sufficient to drive a random graph to equilibrium, the real connectome refuses to resolve. It maintains dynamic tension — oscillating between competing activation states rather than collapsing into one.

This behavior is consistent with multistability: the topology encodes multiple attractors that the system cycles between rather than converging on one. Multistability in a constraint graph is not noise — it is structural. The topology is encoding something that actively resists resolution.

### **Theoretical connection:**

Baggs (2026) locates meaning in the gradient between encoding and retrieval states. A gradient requires persistent difference — a system that resolves has no gradient. A system that refuses to resolve *is* a gradient. The competition model result is the first empirical observation of the real connectome behaving as a gradient-preserving structure: it maintains the tension that the architecture predicts is the locus of structural meaning.

**Conclusion:** Topology governs system-level dynamics under competition, not only propagation magnitude. The real connectome is a structured system. The random graph is a statistical one.

## **9.6 Run 005 — Local Competition Model**

**Configuration:** Real connectome vs. random graph under local competition. Each node normalized against its neighborhood (predecessors + successors) rather than the whole graph. All other parameters identical to Run 004.

**Finding:** The real connectome transitions from a negative mean activation phase, passes through polarity inversion, and stabilizes at a positive mean (+0.013 at step 30, still rising). The random graph drifts weakly, remains near zero throughout, and reaches near-symmetric equilibrium (-0.00009 at step 30). Real connectome variance stabilizes below random (~0.662 vs



~0.674), but exhibits structured progression. Random variance rises smoothly and plateaus earlier.

### **Key finding — conditional stability:**

Run 004 showed the real connectome refuses to resolve under global competition. Run 005 shows it does resolve under local competition — but not trivially. It passes through staged polarity inversion before reaching a structured asymmetric equilibrium. The random graph converges smoothly without transitional reorganization in either condition.

The real connectome is not simply unstable. It is **conditionally stable**: the topology determines the conditions under which coherent convergence is possible, and local interaction is the required condition. Global pressure destabilizes the structure. Local pressure allows it to self-organize.

### **Theoretical connection:**

This two-condition result maps directly onto the gradient mechanism of Baggs (2026). The frozen topology preserves gradient under global constraint (Run 004) and resolves it into organized structure under local constraint (Run 005). Both behaviors are absent in the random graph. Together they demonstrate the topology governing not only the magnitude of output differentiation but the organizational pathway — a property consistent with a constraint field, not merely a biasing network.

The staged polarity inversion — negative phase before positive stabilization — is evidence of multi-stage dynamics: the topology encodes more than one organizational pressure, and those pressures resolve sequentially. This was not designed into the model. It emerges from structure alone, consistent with the limbic boot sequence principle in which lower layers must stabilize before higher layers can organize.

**Conclusion:** Topology determines not just behavior, but the conditions under which stable structure can emerge. Locality is required for coherent convergence. The system is now operating as a constraint-driven dynamical field.

## **9.7 Run 005c — Directed Competition (Methodological Correction)**

**Configuration:** Real connectome vs. random graph under directed local competition. Predecessor-only neighborhoods replace the undirected (predecessor + successor) neighborhoods used in Runs 005/005b. This is a methodological correction: the *C. elegans*

connectome is a directed graph, and undirected neighborhood competition discards the functional asymmetry encoded in edge direction. A synchronous update bug present in the earlier local competition implementation was also corrected. Parameters identical to 005b. 100 steps.

**Finding:** Both systems produce stable, structured dynamics. The real connectome exhibits slightly more damped, regulated behavior — mean activation is more stable, early-phase volatility is lower. The random graph overshoots higher early and shows greater variance. However, no strong real-vs-random separation emerges. Both systems produce bimodal final distributions. Variance converges to near-identical values ( $\sim 0.69$ – $0.70$ ). Polarization indices are similar throughout.

#### **Key finding — instrument diagnosis:**

Directed competition improved the correctness of the implementation. It did not produce strong differentiation. The reason is now understood: directed competition corrects the neighborhood rule but cannot address the fundamental missing component — the HM reference state.

Without HM, there is no prior state to compare against. The gradient mechanism is architecturally absent. The competition rule governs most of the observable behavior. Topology modulates it slightly but cannot express the structured comparison the theory predicts because that comparison requires two components: IM (frozen operator, present) and HM (prior state, absent).

#### **What the weak signal means:**

The Stage 0 model tested IM in isolation and found that structure influences dynamics but does not produce strong independent differentiation. This is the expected result for an IM-only system. The architecture was not designed for IM to operate alone. The weak separation is a limitation of the Stage 0 instrument, not evidence against the architectural claim.

**Conclusion:** Directed competition is the correct implementation of local competition on a directed graph. The absence of strong separation confirms that the gradient mechanism — not directionality alone — is what Stage 1 must introduce.

## 9.8 Scope and Honest Bounds

Stage 0 used simplified propagation models on *C. elegans* — 302 neurons, far below the complexity of any target human-scale implementation. All competition rules are computational approximations, not biologically faithful simulations.

### What Stage 0 establishes:

- Topology alone produces stable, measurable behavioral differentiation without training
- Topology is the primary driver; edge weights are secondary
- Structure governs the pathway and conditions of stabilization, not only final state
- Global competition destabilizes the real connectome; local competition allows coherent self-organization — the topology is conditionally stable
- Directed edge structure produces slightly more regulated dynamics than undirected treatment

### What Stage 0 does not and cannot establish:

- The gradient mechanism — HM was absent from all Stage 0 runs
- Meaningful cognitive differentiation from the encoding-retrieval comparison
- Full validation of the COS retrieval differentiation claim
- Identity-level cognitive differentiation at any scale

### The key limitation:

Stage 0 ran IM in isolation. The encoding-retrieval gradient requires comparison between HM prior state and IM-constrained current state. Without HM, that comparison does not occur. The weak real-vs-random separation in later Stage 0 runs reflects this absence — the competition rule dominated behavior because the gradient mechanism that should complement it was not present. This is a limitation of the experimental design, correctly identified and addressed in Stage 1.

## 9.9 Stage 1 Results — HM-IM Gradient Mechanism (Run 101)

**Configuration:** *C. elegans* connectome (448 nodes, 6625 edges). Persistent reference state introduced as HM analog (reference\_retention=0.90, gradient\_alpha=0.25). Configuration-model-derived random control. 100 steps, seed 42.

**Finding:** Gradient separation between real and random graphs near zero at steps 1-10, building to stable approximately +10% separation by step 31, sustained without reversal through step 100 (70/70 late steps positive). Variance separation +0.145 (steps 50-100).

**Critical observation:** Separation is not present at initialization. It builds over approximately 30 steps and then holds. This temporal buildup is inconsistent with a static distributional artifact (which would be present from step 1) and consistent with the HM reference state accumulating topology-shaped activation history before the structural signal stabilizes.

**Interpretation:** The real connectome sustains higher internal divergence from its own accumulated history than a random graph with the same degree structure. This is the first confirmed operation of the gradient mechanism. It does not prove cognitive differentiation, but it demonstrates that the frozen operator produces persistent state divergence of the kind the architecture requires.

**Conclusion:** Stage 1 hypothesis supported. Gradient mechanism produces real-vs-random separation that emerges over time. This is correctly scoped to HM-IM dynamics in the C. elegans model.

## 9.10 Stage 2 Results — Spatial Geometry Integration (Run 201b)

**Configuration:** Same as Stage 1 with geometry-modulated propagation added: influence = weight  $\times \exp(-\alpha \times \text{distance}) \times \text{state}$ . Biological NML2 positions for 236 neurons; 212 nodes filled with hashlib.md5-derived deterministic synthetic positions. geometry\_alpha=0.5, normalize\_inputs=false (declared removal). Configuration-model-derived control (6380 edges vs 6625 real — disclosed). 100 steps, seed 42. Classification: Valid — Provisional.

**Provisional caveat:** The control is not strictly degree-preserving after self-loop removal (3.7% edge deficit). Early variance separation may partially reflect residual structural differences. Late-emergent gradient separation is treated as the primary structural signal.

### Findings:

Gradient separation (steps 31-100): approximately +9.4%. Comparable to Stage 1. Geometry did not amplify gradient separation beyond Stage 1 levels.

Variance separation (steps 50-100): +0.241, a 66% increase over Stage 1 (+0.145). Geometry substantially amplifies structural heterogeneity — the real connectome resists homogenization more strongly under spatial constraint.

Temporal pattern preserved: separation near zero at initialization, stabilizing after step 30. All 70 late steps positive.

**Interpretation:** Spatial distance attenuation amplifies variance separation without independently strengthening the gradient mechanism. The geometry layer adds constraint heterogeneity (some edges attenuated more than others), which increases the real connectome's internal spread, but does not change the fundamental gradient dynamic established in Stage 1.

**Conclusion:** Stage 2 hypothesis partially supported. Geometry modulates structural differentiation but does not localize it. Global separation persists and strengthens on the variance metric. The pre-registered prediction that geometry would amplify gradient separation was not met; the variance amplification was not predicted and is noted as an empirical finding.

### 9.11 Stage 3 Results — Regional Geometry Field (Run 301)

**Configuration:** Stage 2 model with frozen regional geometry field added at receiving node:  $\text{influence} = \text{weight} \times \exp(-\alpha \times \text{distance}) \times \Phi(v) \times \text{state}(u)$ .  $\Phi$  initialized as  $1 + 0.5 \times \text{region\_score}(v)$ , producing values 1.0 to 1.5. Five spatial regions (k-means clustering on node positions).  $\Phi$  frozen at initialization. Same 448-node coverage, same random control construction, 100 steps, seed 42.

#### Global findings:

Gradient separation (steps 31-100): approximately +11.6%, highest across all stages. All 70 late steps positive. Variance separation +0.248, continued increase from Stage 2.

Directional mean bias: the real graph develops a persistent negative mean activation trend absent in Stage 1 and Stage 2 and absent in the random control. This is a new behavior consistent with non-isotropic constraint accumulation — the geometry field breaks the symmetry present in earlier stages.

#### Regional findings (primary Stage 3 result):

The real graph produces stable regional gradient stratification. Regions 2 and 4 consistently dominate across all three late-phase time windows (steps 31-50, 51-70, 71-100). Region 1 is consistently suppressed. The ordering does not reverse.

The random control, receiving the same geometry field applied to different wiring, produces no stable regional ordering. Regional rankings change completely across windows (window 1: [4,3,1,2,0]; window 2: [1,2,4,3,0]; window 3: [3,4,1,2,0]).

Real dominance range: 0.109 (Region 4 at 1.062 vs Region 1 at 0.952). Random dominance range: 0.103, with no consistent ordering.

#### **Phi-gradient alignment:**

Phi is ordered perfectly by region (1.0, 1.125, 1.25, 1.375, 1.5 for Regions 0-4). The gradient ordering is partially aligned (correlation +0.47) but not monotonic. Region 3 (Phi=1.375) does not rank third — it performs mid-tier while Regions 2 and 4 dominate.

This partial alignment is theoretically informative. It indicates that Phi modulates input at the receiving node, but topology determines whether that amplification is sustained. Region 3 carries higher Phi but its wiring structure does not produce the feedback dynamics that allow amplification to persist. The geometry field does not override topology — it operates through it.

#### **Falsification assessment:**

Pre-registered failure condition 1 (no regional differentiation): not met. Pre-registered failure condition 2 (non-persistent structure): not met. Pre-registered failure condition 3 (no Phi alignment): partially met — alignment is moderate, which supports the topology-gates-geometry interpretation. Pre-registered failure condition 4 (control equivalence): not met.

**Conclusion:** Stage 3 primary hypothesis confirmed. The frozen operator with a regional geometry field produces stable, spatially anchored internal hierarchy absent in the random control. This is the first result in which the system demonstrates region-dependent behavior without modifying the structural operator over time. The mechanism is not Phi alone — it is the interaction between the geometry field and the specific wiring structure of the real connectome.

### **9.12 Cross-Stage Summary**

The four completed experimental stages establish a coherent progression:

**Stage 0** confirmed that topology alone shapes dynamics without training. Topology is the primary driver; edge weights are secondary.

**Stage 1** confirmed the gradient mechanism. A persistent reference state produces topology-dependent gradient separation that builds over time, consistent with structural rather than distributional origins.

**Stage 2** confirmed that spatial geometry amplifies structural heterogeneity. Variance separation increased substantially; gradient separation remained comparable to Stage 1. Geometry adds constraint heterogeneity without independently strengthening the gradient dynamic.

**Stage 3** confirmed regional localization. A frozen geometry field produces stable regional gradient stratification in the real graph absent in the random control. Topology mediates where geometry is expressed. This is the first evidence of spatially anchored internal hierarchy emerging from a frozen operator.

The trajectory is: topology shapes dynamics; the gradient mechanism produces persistent divergence from accumulated history; spatial geometry amplifies and then localizes that divergence into stable regional structure.

### 9.13 Stage 3B Results -- Anatomical Gradient Validation

**Configuration:** Post-run analysis of Run 301 outputs. No new simulation. Steady-state gradient field (steps 31-100) embedded into biological coordinate space and tested against anatomically defined WormBase classifications using 1000 seeded permutations (seed=42). 236 biological nodes (NML2 positions); 212 hash-fill nodes excluded from statistical test.

#### Statistical results:

Three anatomical classes exceed the null maximum across all 1000 permutations ( $p_{\text{adjusted}} = 0.000$ ):

Class	Grad Mean	Dominance	$p_{\text{adjusted}}$
posterior_ganglia	0.9087	1.085	0.000
motor_ventral_cord	0.8918	1.065	0.000
interneuron_cord	0.8867	1.059	0.000
interneuron_ring	0.8175	0.976	1.000

Class	Grad Mean	Dominance	p_adjusted
sensory	0.8326	0.994	1.000

Gradient-degree correlation:  $r = -0.060$  ( $p = 0.362$ ). No degree-driven artifact.

### Key finding:

Ring interneurons carry the highest mean degree (152.4) of any anatomical class and produce the lowest gradient dominance (0.976, below global mean). The most connected neurons show the weakest departure from accumulated history. This is the anatomical class-level confirmation of R1.

### Critical interpretation:

Stage 3B establishes that constraint-gradient propagation does not reconstruct spatial anatomy. It reveals regions of maximal structural influence within the system. Posterior ganglia and cord interneurons are gradient-dominant not because of their spatial position but because of their structural position in the frozen operator's propagation hierarchy. This principle governs interpretation of all future COS stage outputs.

### Core principle established:

Constraint fields do not preserve spatial form. They reveal regions of maximal structural influence within a system.

**Validation condition V1:** Satisfied. Stage 3B formally validated.

## 9.14 Stage 4 Results -- FlyWire Scale + Signed Synaptic Constraint (Run 401)

**Configuration:** FlyWire FAFB v783. 127,536 nodes, 3,667,720 edges (largest strongly connected component). Signed type modifier applied at the pre-synaptic neuron: excitatory = +1.0, inhibitory = -1.0, unknown = +1.0. Type derived from Eckstein et al. neurotransmitter predictions (neuron-level, not edge-level). Distance attenuation applied (geometry\_alpha = 0.5). Phi field excluded. Configuration-model-derived random control with shuffled weight distribution. 100 steps, seed 42.

**Edge type distribution:** excitatory 68.0%, inhibitory 19.9%, unknown 12.1%. E/I ratio 3.41:1.



### **Primary finding -- dynamical bifurcation:**

The real and random graphs do not differ in gradient magnitude. They differ in dynamical regime.

The real graph builds gradient from near-zero at step 1 to stable 0.076 by step 31. It holds there through step 100 without decay or oscillation.

The random graph follows the same early buildup. Then it collapses. Gradient reaches zero at step 23. It stays at zero for all remaining steps (31-100: 70/70 steps at zero). Variance also collapses to zero -- all nodes converge to identical activation. The system reached a fixed point and stopped.

Both graphs exhibit similar early-phase gradient buildup. The divergence emerges as the reference state accumulates, revealing a topology-dependent transition between sustained dynamics and equilibrium collapse.

This is not a larger version of the Stage 1-3 result. Stages 1-3 showed the real graph sustaining 10-12% higher gradient than random. Stage 4 shows the real graph sustaining gradient while the random graph produces none. These are different classes of result.

### **What this rules out:**

The random control preserves the real graph's degree sequence, weight distribution, and type assignments per node. The collapse therefore cannot be explained by degree, weight, or type count differences. The specific wiring of the real connectome is what sustains dynamics. Rewiring it -- while keeping everything else -- destroys the property.

### **Signed input mean:**

Real graph: -7.23 (steps 31-100). Random: approximately zero.

The real system is continuously driven away from equilibrium by its own topology. The negative signed input mean reflects a state-dependent drive produced by how the specific topology pairs excitatory and inhibitory inputs. It is not static inhibitory dominance -- it depends on current state. But the topology sustains it step after step. The random graph has no equivalent drive. Its net input is zero because local E/I contributions cancel.

### **Type balance:**

Real type\_balance: 0.200 (stable, steps 31-100). Random: collapses to 0.0 for 55 of 70 late steps (because all contributions are zero when states are zero).

With identical type assignments, the real topology sustains non-cancelling excitatory dominance in input magnitude. The random topology cannot.

### **No oscillatory instability:**

The pre-registered failure mode did not occur. Gradient did not oscillate. The tanh bounding held at 127k-node scale with signed constraint.

### **No directional mean bias:**

Stage 3 produced a persistent negative mean activation drift under the geometry field. Stage 4 shows mean oscillating near zero with no directional trend. Geometry breaks the symmetry of state. Signed constraint breaks the symmetry of constraint. These are different mechanisms with different observable effects.

### **Mechanistic statement:**

The real connectome encodes non-uniform excitatory–inhibitory input structure that does not cancel under signed constraint. Rewiring the graph while preserving degree, weight, and type distributions destroys this structure. Local E/I inputs then balance, the reference state catches up, and the system converges to a fixed point. Sustained gradient therefore depends on the specific topology-type interaction -- not on complexity, degree, or type counts alone.

**Classification:** Valid. Protocol followed. All pre-registered failure modes tested and not observed. Random collapse is a valid result -- a correctly executed null result is more valuable than an incorrectly executed positive result.

Stage 4 demonstrates a regime transition: under signed constraint, topology determines whether the system converges to equilibrium or sustains non-equilibrium dynamics. This is a qualitative shift from the magnitude-based differentiation observed in Stages 1–3.

## **10. Limbic Boot Sequence**

Empirical neuroscience establishes that limbic structures evaluate sensory input before cortical awareness registers it (LeDoux). Patients with bilateral limbic damage retain cortical function

but lose decision capacity — valuation collapse produces total system failure, not graceful degradation (Damasio). The evolutionary layering of reptilian core, limbic layer, and neocortex defines each layer as foundational to the one above (MacLean).

The COS architecture formalizes this as a five-stage operational prerequisite:

**Stage 1 — Limbic Core:** Amygdala, hippocampus, hypothalamus. Affective baseline, salience system, autonomic regulation. Kernel — all other stages depend on this.

**Stage 2 — Integration:** Cingulate cortex, orbitofrontal cortex. Emotion-to-cognition bridge, conflict monitoring, motivational direction.

**Stage 3 — Associative:** Temporal-parietal junction. Semantic binding, concept integration, language processing.

**Stage 4 — Executive:** Prefrontal cortex. Decision architecture, planning, evaluation.

**Stage 5 — Identity:** Default mode network. Self-reference, narrative coherence.

This defines the correct implementation sequence: build and validate each layer against the running layer below before adding the next.

## 11. Relation to Concurrent Work

Shiu et al. (2024) demonstrated that a leaky integrate-and-fire model built from the FlyWire connectome predicts sensorimotor behavior with high accuracy. Eon Systems (2026) extended this by connecting the brain model to a physics-based virtual body in a closed sensorimotor loop.

These results establish that connectome topology carries functional information. The COS architecture builds on that empirical grounding without replicating it. The distinction is precise: Shiu et al. and Eon Systems use topology as a basis for behavioral emulation, supplemented by pre-trained controllers. COS uses topology as a retrieval and prioritization constraint operator, explicitly without training on top.

The claim is not behavioral fidelity. The claim is retrieval differentiation. These are different experimental targets.

**Network Neuroscience Theory and the topology of intelligence.** Wilcox et al. (2026) tested the Network Neuroscience Theory (NNT) of general intelligence in 831 participants from the Human Connectome Project, with conceptual replication in an independent sample of 145 participants. Their investigation demonstrated that general intelligence depends on four global topological properties of the human connectome: distributed processing across multiple networks; weak, long-range connections enabling system-wide communication; modal control regions that orchestrate network activity by driving the system toward difficult-to-reach states; and small-world architecture balancing local clustering with global path efficiency. Critically, lesion analyses showed that removing any single network produced negligible change in predictive performance, while the whole-brain model consistently outperformed all single-network models -- indicating that between-network connections, not localized regions, drive the structural basis of intelligence.

These findings provide direct empirical support for the theoretical position the COS architecture operationalizes. The gradient mechanism's behavior aligns with the weak tie result: long-range connections are precisely where current activation is most likely to depart from accumulated local history, sustaining gradient rather than allowing rapid equilibration. The modal control finding -- that regions capable of driving the system toward non-default states predict  $g$  -- corresponds to nodes exhibiting persistently high gradient magnitude in Stage 3 of the COS validation. The small-world result aligns with the consistent finding across all COS stages that real connectome topology resists homogenization relative to random controls.

The COS architecture is the experimental complement to NNT's correlational findings. NNT demonstrates that global connectome topology correlates with measured intelligence. COS tests whether a frozen structural operator derived from biological connectome topology is causally sufficient to produce stable, topology-dependent differentiation -- without behavioral data, functional imaging, or training.

## 12. Limitations

- Stage 2 spatial geometry used partial biological positions (236/448 nodes); 212 nodes received deterministic synthetic positions. Full biological spatial embedding has not been tested.
- Stage 3 geometry field used k-means spatial clustering for region definition. Stage 3B replaced k-means with WormBase anatomical classifications and confirmed statistically significant gradient concentration in posterior ganglia, cord interneurons, and motor ventral cord ( $p_{\text{adjusted}} < 0.0001$  against 1000 seeded permutations).
- Phi-gradient alignment in Stage 3 is moderate (+0.47). Topology mediates geometry expression; the interaction is not fully characterized.

- The configuration-model-derived random control is not strictly degree- preserving after self-loop removal. Early-time variance separation may partially reflect residual structural differences.
- Gradient separation magnitude at *C. elegans* scale (approximately 10% in Stage 1, 11.6% in Stage 3) does not establish that separation will be functionally meaningful at human-scale knowledge retrieval. Whether small but consistent topological differentiation produces behaviorally distinguishable outputs under a full HM architecture is a Tier 3 claim not yet testable at current implementation scale.
- Long-duration stability of the frozen operator under high-variance or high-dimensional input has not been tested. All validation runs used 100 steps on small graphs. Whether the gradient mechanism maintains stable separation over extended operation without saturation or dead-loop convergence is an open empirical question.
- Stage 4 introduces inhibitory constraint polarity for the first time. The stability of tanh-bounded signed propagation under real excitatory-inhibitory imbalance is untested. Gradient collapse or oscillatory instability in Stage 4 would constitute a falsification condition for the signed constraint hypothesis, and would additionally indicate that biological E-I balance is a functional requirement rather than an implementation detail of the architecture.

### 13. Interpretation

The COS architecture should be understood as:

A method for introducing persistent, structure-driven differentiation into otherwise shared knowledge systems — through the comparison of prior accumulated state against current structurally constrained input.

It is not yet a model of full cognition or consciousness. It is a structured derivation from prior theory, with staged implementation, preliminary empirical support, and explicit falsifiability conditions.

Stage 0 established that the precondition holds: topology influences dynamics, and this influence is real, consistent, and not reducible to edge weights. What Stage 0 could not establish — and was not designed to establish — is whether the gradient mechanism produces the differentiation the theory predicts. That requires HM. Stage 0 ran without it.

The correct reading of Stage 0 is not "weak results." It is: the instrument confirmed the precondition and identified the boundary where the next component is required. That is what a staged model is supposed to reveal.

## 14. Conclusion

The Connectome-as-Operating-System architecture proposes that fixed structural topology can act as a constraint operator over a shared knowledge base, producing stable differences in interpretation and prioritization — through the comparison of prior accumulated state (HM) against current structurally constrained input (IM(CLM)).

Four experimental stages have now been completed using the *C. elegans* connectome.

Stage 0 established the precondition: topology influences dynamics, topology is the primary driver over edge weights, and structure governs stabilization pathways. Stage 0 ran without HM and cannot establish the gradient mechanism.

Stage 1 confirmed the gradient mechanism. A persistent reference state (HM analog) introduced into the system produces approximately 10% higher gradient magnitude in the real connectome than in a matched random control. The separation emerges over time rather than at initialization, consistent with topology-driven accumulation.

Stage 2 confirmed that spatial geometry amplifies structural heterogeneity. Variance separation increased 66% over Stage 1 under distance-modulated propagation. Gradient separation remained comparable, indicating that spatial geometry adds constraint heterogeneity without independently strengthening the gradient dynamic.

Stage 3 confirmed regional localization. A frozen regional geometry field produces stable gradient stratification across spatial regions in the real connectome, absent in the random control. This is the first result in which the system demonstrates region-dependent behavior — spatially anchored internal hierarchy — without modifying the structural operator over time. Moderate Phi-gradient alignment and Region 3 underperformance confirm that topology mediates where geometry is expressed: the geometry field modulates, but wiring structure determines where modulation persists.

The progression from Stage 0 through Stage 3 establishes the following: topology shapes dynamics; the gradient mechanism produces persistent divergence from accumulated history; spatial geometry amplifies that divergence; a regional geometry field localizes it into stable spatial hierarchy.

Stage 3B converted the informal spatial observation into a formal statistical test, confirming that the Run 301 gradient field shows non-random concentration in anatomically defined

high-integration regions. Three classes -- posterior ganglia, cord interneurons, and motor ventral cord -- exceeded the null maximum across all 1000 seeded permutations. Ring interneurons, despite carrying the highest mean degree of any anatomical class, show below-average gradient dominance -- the anatomical class-level confirmation that gradient is not driven by connectivity. This result establishes a foundational interpretive constraint: constraint fields do not preserve spatial form. They reveal regions of maximal structural influence within a system.

Stage 4 introduced signed synaptic constraint at FlyWire scale (127,536 neurons). The result was not a larger version of the gradient separation observed in Stages 1-3. The real connectome sustained active gradient dynamics for all 100 steps. The random control -- with identical degree sequence, weight distribution, and type assignments -- collapsed to zero by step 23 and never recovered. This is a topology-dependent bifurcation between sustained non-equilibrium dynamics and equilibrium collapse. Signed constraint does not just increase separation. It reveals whether a topology can sustain dynamics at all under directional constraint.

The immediate goal is not to replicate minds. It is to demonstrate that a frozen structural operator, operating with a persistent prior state and a spatial constraint field, produces measurable, stable, and spatially organized differentiation. That demonstration is now in place at the scale of *C. elegans* and at the scale of the *Drosophila* brain. The next experimental target is biological topology with limbic-dominant structure, moving toward a constraint operator that reflects the layered architecture the theory requires.

The world the operator accesses grows. The structural constraint the operator applies does not change. The comparison between what was and what is, mediated by frozen structure, is the mechanism. That is the design principle.

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